Artificial Intelligence for Sustainable Development

Thomas G. Dietterich
Professor (Emeritus)
Oregon State University

Developed vs. Developing World

Share the Same Goals

- Smart Economy
  - Smart Agriculture
- Smart Transportation
- Smart Health
- Smart Government
  - Smart Cities
- Etc.

Developing Country Constraints

- Scarce Financial Resources
- Larger Informal Economy
- Shortage of Expertise in All Areas
- Often More Vulnerable to Climate Change
- Etc.

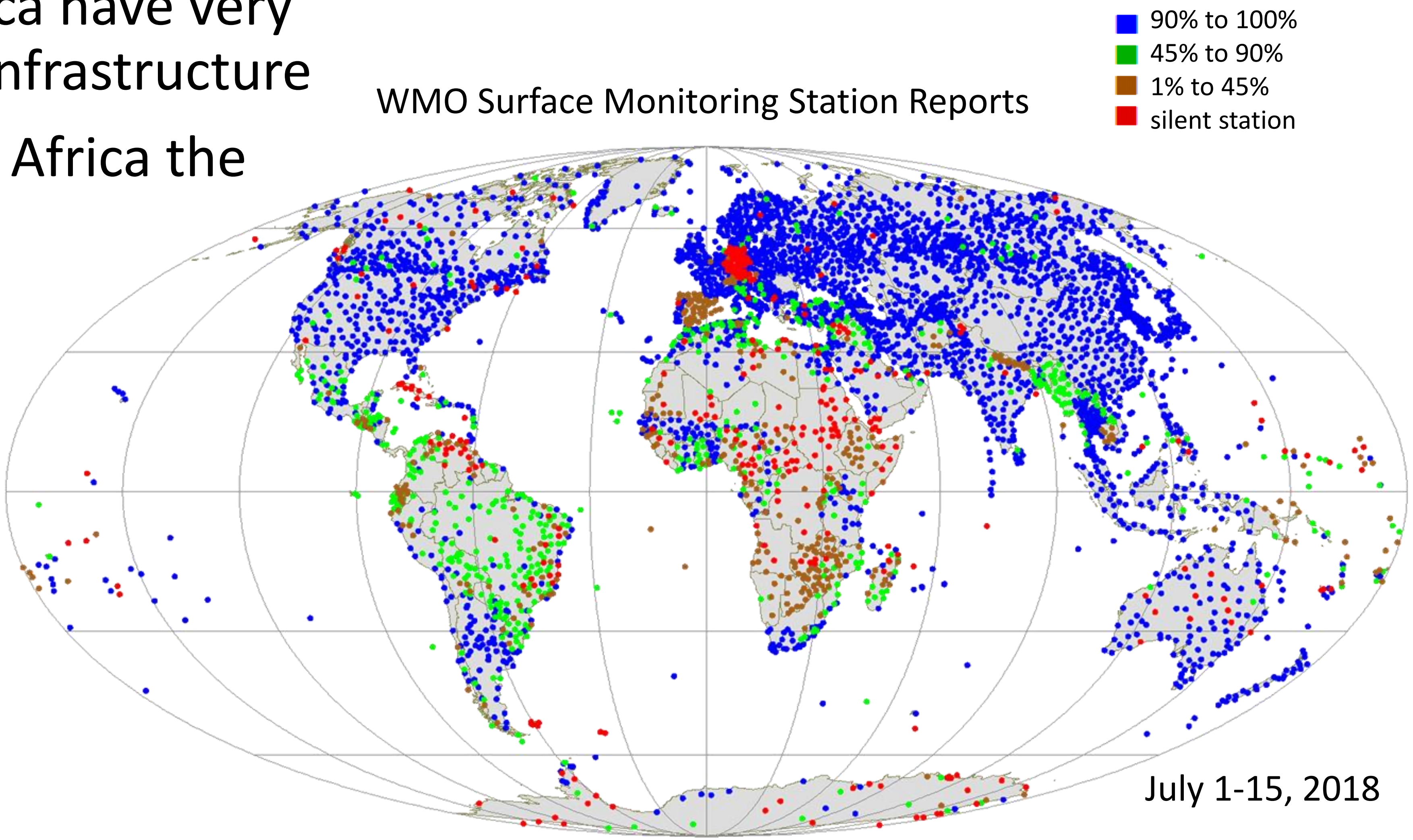
Three Major Themes

1. Collecting Better Data for Better Decisions
2. Compensating for Lack of Experts
3. Allocating Scarce Resources

Source: Quinn, J., Frias-Martinez, V., & Subramanian, L. (2014). Computational sustainability and artificial intelligence in the developing world. *AI Magazine*, *35*(3), 36.

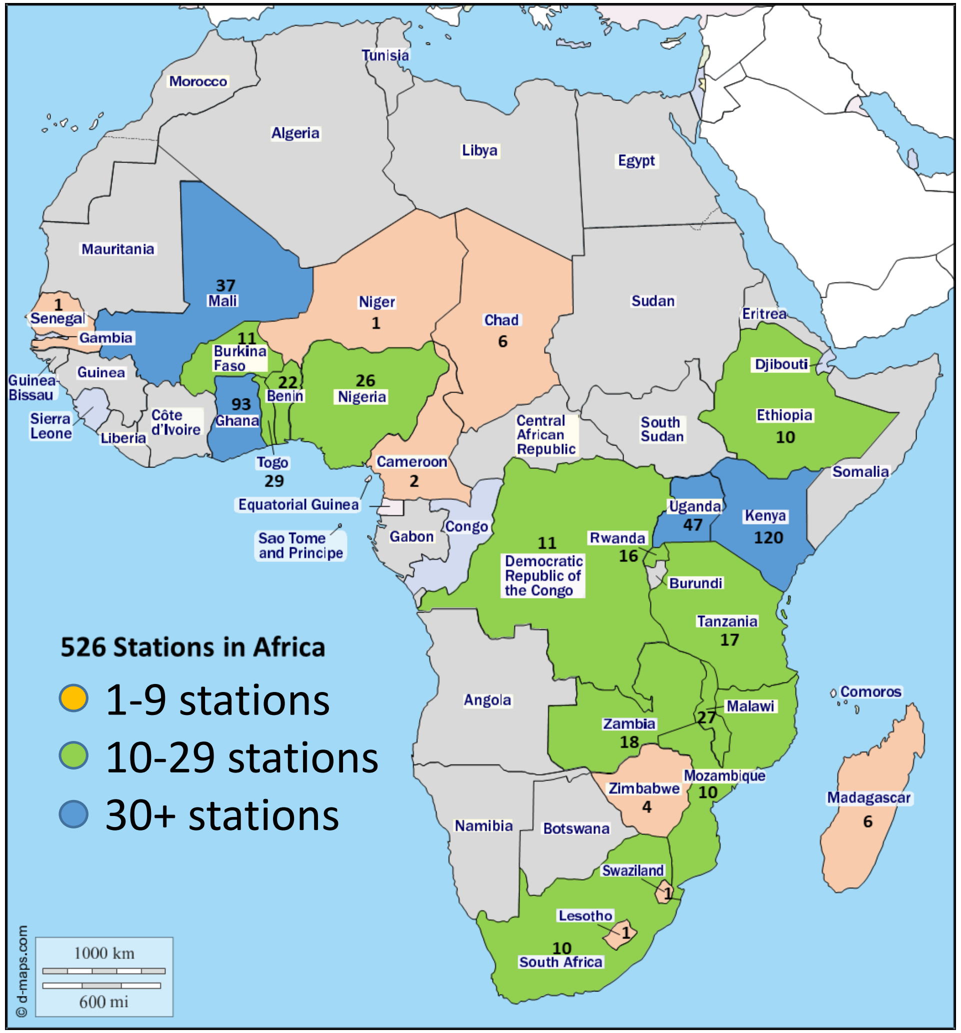
Data Gathering (1): TAHMO

- Africa and Latin America have very poor weather station infrastructure
- TAHMO seeks to make Africa the best-sensed continent



Trans-African HydroMeterological Observatory

- TAHMO.ORG seeks to be a self-sustaining, non-profit company
- Deploy and operate a network of 20,000 automated weather stations throughout all of sub-Saharan Africa
- 526 stations in Africa
- 33 Stations in Nigeria
  - Proposal pending with HIS Towers to add 200 more stations in 2020



https://d-maps.com/carte.php?num_car=25458

AI Challenge: Data Quality Control

- Weather Sensors Fail
  - Solar radiation sensor gets dirty
  - Wind sensors (anemometers) get dirty or blocked
  - Rain gauge becomes obstructed
  - Novel failures occur often

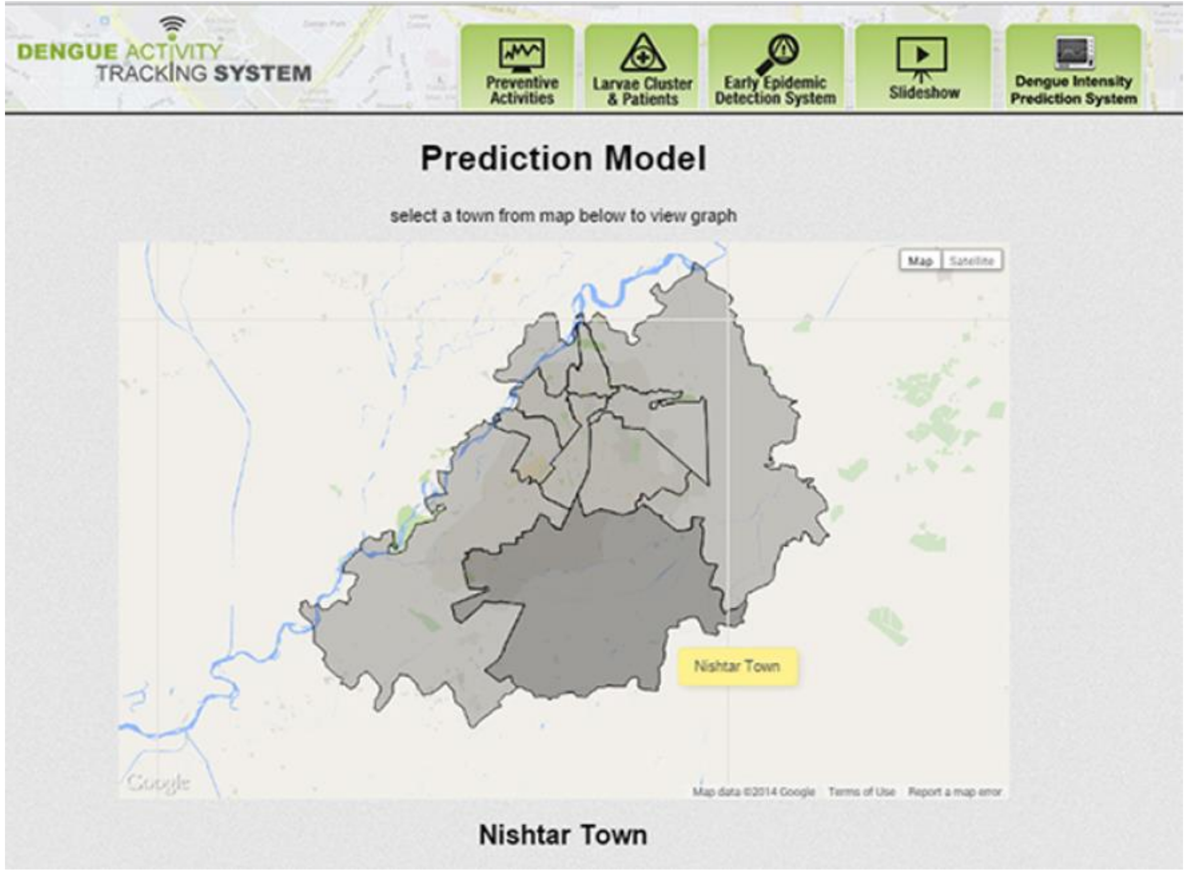
- AI for Quality Control
  - Train Anomaly Detectors to recognize abnormal sensor readings
    - no rainfall when all neighboring stations report rain
    - sudden drop in temperature
    - relative humidity that increases when temperature increases
  - Issue Alarms
    - technician visits station to clean and make repairs

Ant Infestation

Data Gathering (2): Dengue Monitoring and Forecasting

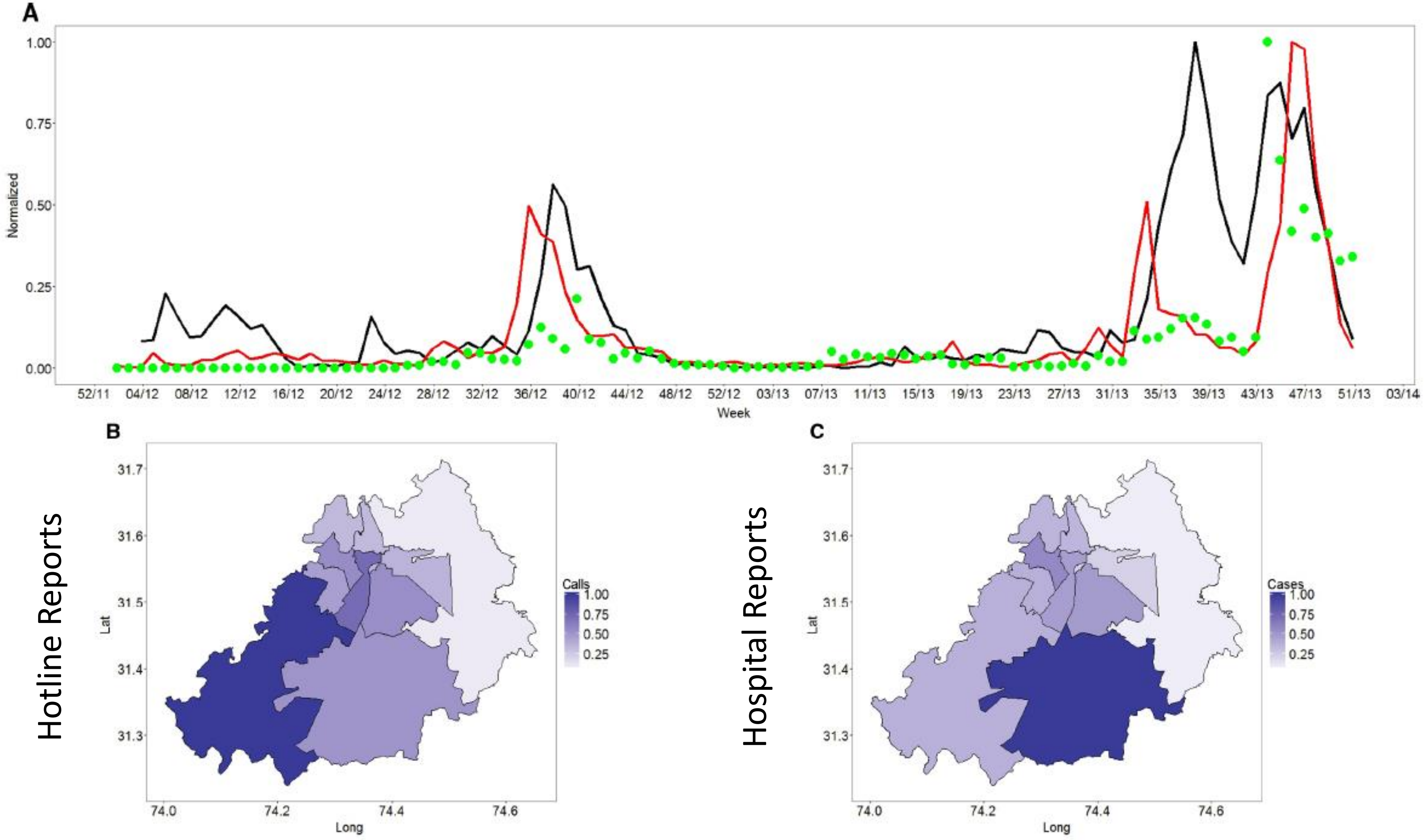
Rehman, et al. Science Advances, 2, 2016

- Goal: Detect Dengue outbreaks early and prioritize interventions
  - garbage collection
  - sewage leaks
  - insecticide spraying
- Data:
  - Health Symptom Hotline
    - people call in to ask about their symptoms
      - dengue, malaria, etc.
  - Weather Data (weekly, city-level)
  - Hotline Awareness Campaigns
- Status:
  - Deployed in Lahore, Pakistan since 2013

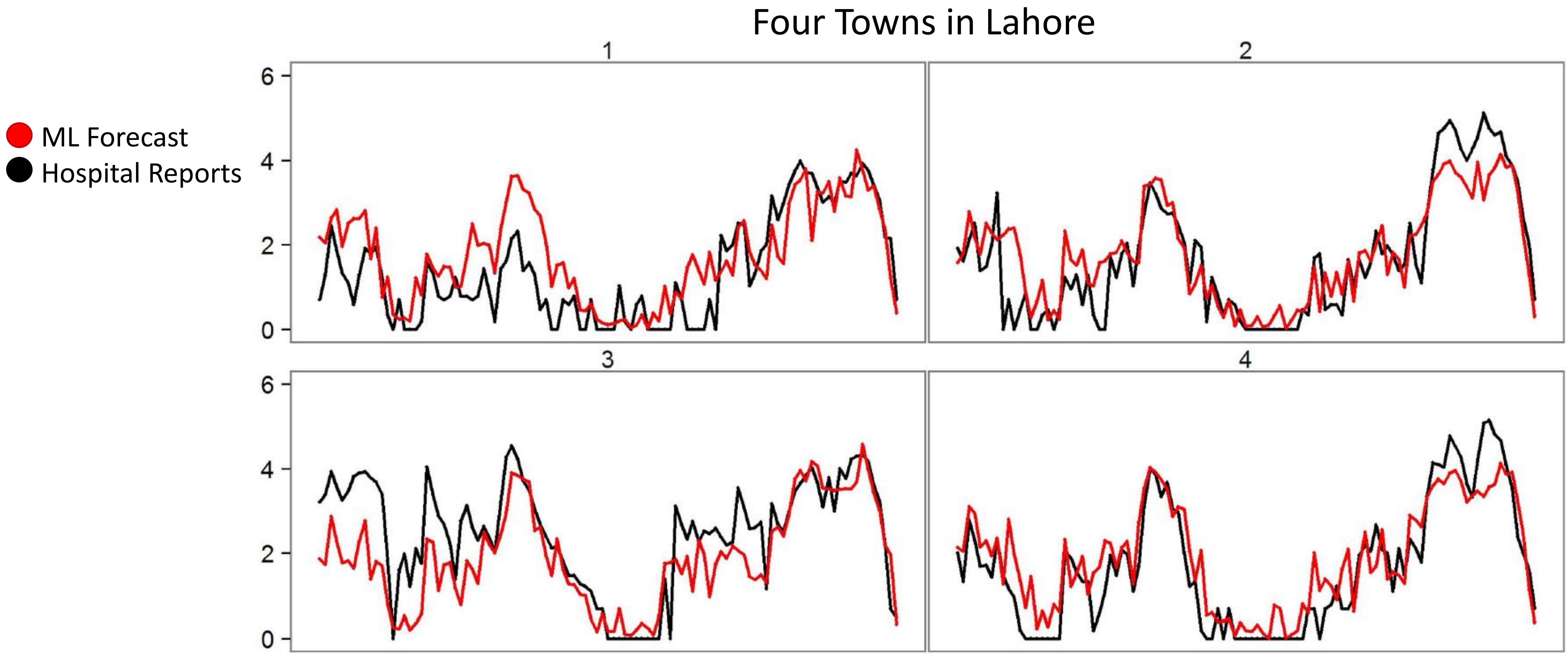


Hotline Reports Predict Hospital Reports Two Weeks Into the Future

- Hotline Reports
- Hospital Reports
- Awareness Events



Machine Learning Model Forecasts

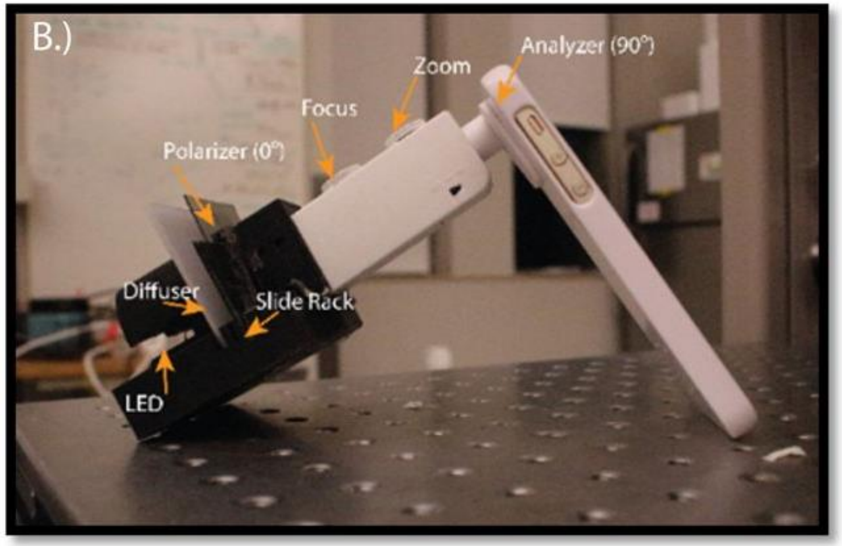


More Examples

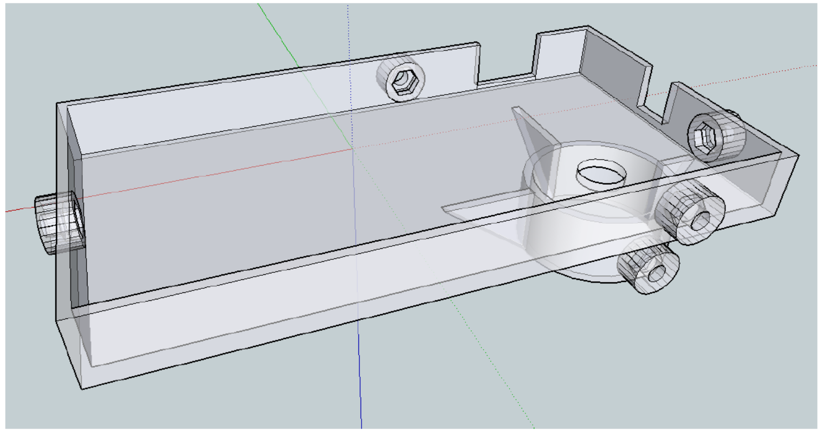
- Traffic congestion monitoring using solar-powered camera phones (Kampala)
- Measuring effectiveness of H1N1 flu quarantine using cell phone call data records (Mexico)
- Poverty Mapping via satellite remote sensing (Worldwide)

Compensating for Lack of Experts: Malaria Diagnosis

- Microscopic examination of blood smears is the gold standard for malaria diagnosis, but there is a lack of trained personnel
  - Uganda: 66% of lab staff positions are vacant
- Solution: Computer vision
- Several R&D groups have developed cell-phone based methods for capturing images of blood smear slides
  - some attach hardware to the phone
  - some attach phone to existing microscopes



External lens & polarizer (Pirnstill & Cote, Nature, 2015)



3D printed microscope adapter (Quinn, et al. 2014)

Computer Vision Performance on Microscope Images

- Limit of Detection (LoD): How many parasites per μL of blood can be detected with 90% specificity at 90% sensitivity?

Team	Blood Volume μL blood	Limit of Detection $p/\mu L$
WHO level 1 expert	0.03-0.07	100
Quinn, et al. (2014)	0.06	4800
Rosado, et al. (2016)	0.04	6640
Linder, et al. (2014)	0.05	9400
Diaz, et al. (2009)	0.005	12800
Delahunt, et al. (2015)	0.1	267
Mehania, et al. (2017)	0.1	112

Current Research Directions

- Polarizing Light to detect Malaria Hemozoin crystals
  - Pirnstill & Cote, 2015
- Microfluidics using qPCR
  - Warkiani, et a. 2015

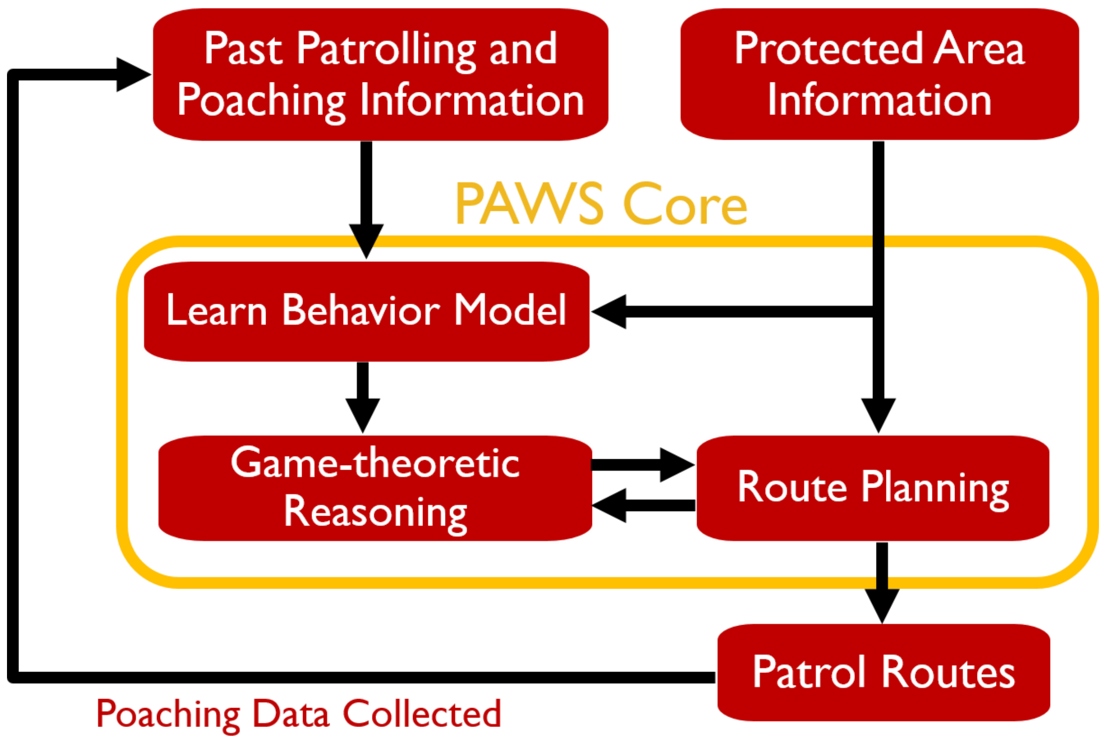
- Goal: Point-of-Care Diagnosis
  - stable and inexpensive chemical agents
  - low power computation
  - no cloud computing (no network connection needed)
  - diagnose multiple diseases

- Applications in Agriculture
  - Diagnosing cassava diseases

Allocating Scarce Resources: Anti-Poaching

- Problem: Wildlife Poaching in National Parks
- Scarce Resource: Game Wardens
- Method:
  - Forecast where poaching attacks will take place
    - Animal behavior model
    - Poacher behavior model
  - Solve a "security game" to design patrol routes that cover likely attack locations while being very unpredictable
  - Plan feasible routes along ridges and streams (avoid large altitude changes, obey time limits, start/end at base camp)
- Deployments
  - Tested in Queen Elizabeth National Park, Uganda (African elephant)
  - Deployed in Malaysia (Asian tiger, Asian elephant)

PAWS: Protection Assistant for Wildlife Security



Fang, et al. USC and Carnegie Mellon University

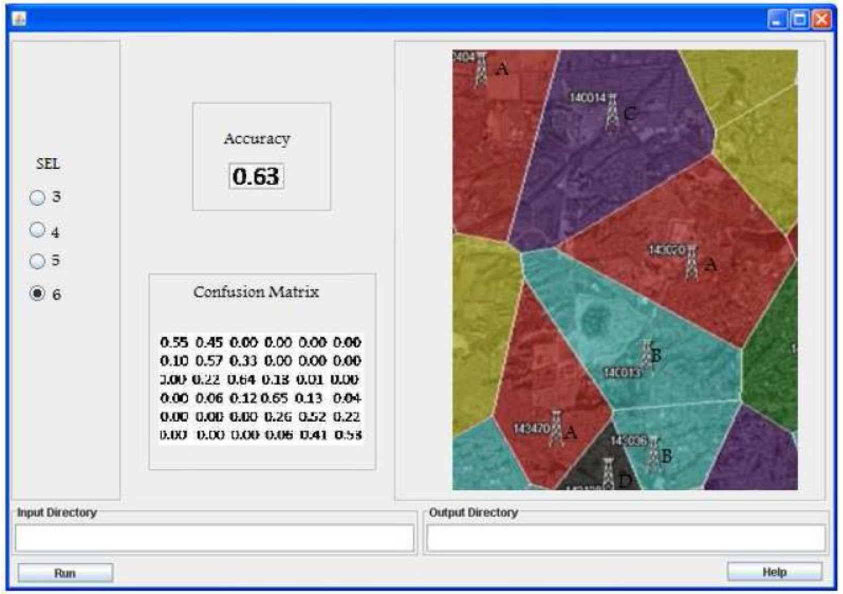
Many Applications of Security Games

- Air Passenger Security at Los Angeles International Airport (LAX)
- US Coast Guard security in NY, Boston, San Francisco Harbors
- US Coast Guard Fisheries Enforcement in Gulf of Mexico
- Los Angeles Police Department
- US Federal Air Marshals Service

Reducing the Cost of Government Census-taking

- Problem: Collect household socio-economic data as part of national census
- Scarce Resource: Census workers
- Approach "CenCell":
  - Use cell phone call records to predict socio-economic variables
    - Number and duration of calls
    - Social network structure (each call is a link between two phones)
    - Mobility of the phone
  - Use results from previous census to train a machine learning model to predict the socio-economic census variables for geographical census units
- Result: Accurate socio-economic maps and population estimates for unnamed Latin American city
- Future Work on Resource Allocation
  - Replace exhaustive census (full enumeration) with smart sampling
  - Cluster census units into groups with similar socio-economic levels
  - Allocate census workers to a representative sample of households within each group

CenCell User Interface



Summary

1. Collecting Better Data for Better Decisions
   - Weather data (TAHMO)
   - Dengue Monitoring
2. Compensating for Lack of Experts
   - Point-of-care malaria diagnosis
3. Allocating Scarce Resources
   - Security Games for law enforcement (PAWS, anti-poaching)
   - Cheaper, more accurate census estimates

References

- Fang, F., et al. PAWS: Protection Assistant for Wildlife Security. http://teamcore.usc.edu/people/Paws/index.html
- Frias-Martinez, V., Soto, V., Virseda, J., Frias-Martinez, E. (2012). Computing Cost-Effective Census Maps from Cell Phone Traces. *Second Workshop on Pervasive Urban Applications*, Newcastle, UK, June 19.
- Mahanian, C., et al. (2017). Computer-Automated Malaria Diagnosis and Quantitation Using Convolutional Neural Networks. *International Conference on Computer Vision (ICCV-2017)*, 116-125.
- Pirnstill, C. W., Coté, G. L. (2015). Malaria Diagnosis Using a Mobile Phone Polarized Microscope. *Nature Scientific Reports, 5* (13368).
- Quinn, J. A., Andama, A., Munabi, I., Kiwanuka, F. N. (2014). Automated Blood Smear Analysis for Mobile Malaria Diagnosis. In *Mobile Point-of-Care Monitors and Diagnostic Device Design*, ed. W. Karlen and K. Iniewski. Boca Raton, FL: CRC Press.
- Quinn, J., Frias-Martinez, V., Subramanian, L. (2014). Computational Sustainability and Artificial Intelligence in the Developing World. *AI Magazine*, Fall, 36-47.
- Warkiani, M. E., Tay, A. K. P., Khoo, B. L., Xu, X., Han, J., Lim, C. T. (2015) Malaria detection using inertial microfluidics. Lab on a Chip (4), 2015.